Advancing the Toxics Mobility Inventory: Development and Application of a Toxics Mobility Vulnerability Index to Harris County, Texas

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Abstract

Harris County, Texas, is home to thousands of documented sources of environmental pollution. It is also highly vulnerable to impacts from natural hazards, including floods. Building on the Toxics Mobility Inventory (TMI), this article discusses how the authors developed a Toxics Mobility Vulnerability Index (TMVI) and applied it to Harris County to assess potential exposure risks to residents from the transfer of toxic materials during flood events. The TMI concept was operationalized and standardized by combining multiple spatial data sets to simultaneously evaluate various factors in the weather hazards—extant toxics—social vulnerability nexus (e.g., floodplain area, industrial land use, social vulnerability measures). Findings indicated hot spots of vulnerability to hazard-induced toxics transfer concentrated in Northeast Houston US Census tracts in Harris County. The main drivers of increased risk in these areas include the proportion of the area that is impervious surface, consistently high social vulnerabilities, and poor health. However, the most vulnerable areas also have overlapping exposure to both industrial land use and floodplains. Assessing the contribution of a set of industrial land use, social vulnerability, natural hazard, emergency response, and topography variables in a single index on the same spatial scale (e.g., US Census tract) provides detailed information for policy makers tasked with mitigating risk. Applying tools such as the TMVI to highly vulnerable urban and coastal locations may help identify changes needed for preparedness and mitigation planning and highlight areas where limited resources for investment- and policy-related remediation should be focused, both before and after disasters.

Keywords: coastal; mobilization; natural hazards; pollution

Introduction

The Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) of 1980 authorized the US Environmental Protection Agency (US EPA) to identify, prioritize, and remediate sites contaminated with hazardous waste and required responsible parties to conduct cleanup activities or provide reimbursement for costs associated with clean-up.[1] Sites with confirmed or potential hazardous releases are screened and, if further investigation is deemed necessary, placed on the National Priorities List (NPL) of Superfund sites.[1] Currently, there are more than 1,330 active and 50 proposed NPL Superfund sites in the United States.[2] Approximately 60 percent of NPL sites are at risk for climate change-related disaster events such as sea level rise, flooding, storm surge, and wildfire.[3] However, there are disparities among residents who live near these sites, areas known as environmental justice neighborhoods, in terms of their awareness of environmental hazards[4] and their vulnerability to the health impacts of toxic chemical exposures.[5]

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The convergence of natural disasters and environmental contamination from anthropogenic sources heightens the potential for toxicant mobility and transfer, as evidenced by temporal changes in soil-borne contaminant concentrations associated with flooding events such as Hurricanes Katrina and Harvey.[6,7] In 2016, an estimated 53 million US residents—16 percent of the total population—lived within three miles of a Superfund remediation site.[8] Compared to the US population as a whole, areas in close proximity to Superfund remediation sites have disproportionately larger proportions of minority residents, individuals who have not completed high school, households with incomes below the level of poverty, and linguistically-isolated households.[8]

Minority and low-income populations are also inequitably exposed to hazardous sites that are not included in the NPL.[9] For example, among large polluters required to report the quantity of both emissions and chemicals sent to landfills as part of the Toxic Release Inventory, the facilities are disproportionately located in low-income census tracts and there is a high correlation between emission intensity and the population density of people of color.[10]

According to the US Global Climate Change Research Program,[11] extreme climate- and weather-related disaster events are expected to increase in both frequency and intensity. From 1980 to 2020, there were 273 billion-dollar disaster events in the United States, with a total cost of $1.79 trillion.[12]

The challenges associated with current and projected weather- and climate-related disaster events differ by geographic region, with coastal and urban areas being especially prone.[11] As a Gulf Coast state, Texas is highly susceptible to hurricanes and tropical storms, sea level rise, inland flooding, stormwater inundation, and other large-scale catastrophic disaster events; 43 percent (114 of 273) of all billion-dollar disaster events in the past 40 years have occurred in Texas.[12] Severe storms were the most frequent billion-dollar disaster type, accounting for 57 percent of all events in Texas and 44 percent of all events nationally.[12]

In addition to the natural hazard vulnerabilities associated with its coastal location, Texas is home to the nation's largest petrochemical complex, located along the Houston Ship Channel.[13] Hazard vulnerabilities and industrial density interact synergistically with a highly socially vulnerable population that lives and works in coastal Texas.[14–16] These social vulnerabilities (e.g., poverty, disability, isolation, overcrowding, limited proficiency in the official or dominant language) limit an individual's or group's ability to respond to, cope with, and recover from a disaster.[17]

Severe storms and associated flooding are among the most deadly and destructive natural hazards affecting the United States, accounting for more than 80 fatalities and nearly $8 billion in damages in an average year.[18] Flooding is also a leading contributor to the spread of toxic materials across communities, including toxicants such as chemicals from current or former hazardous land uses.[19] During a flood event, water can facilitate contaminant transport and fate, moving toxicants from places where they have been concentrated (e.g., industrial facilities) and transferring them to other areas, including residential neighborhoods, where they can have deleterious effects on residents' health and their environment.

Floodwaters do not respect zoning boundaries, property lines, or differences in land-use designation, especially when present in large volumes or moving at high velocity. Flood mitigation measures, if they exist at all, are frequently inadequate to prevent the spread of toxics.[20] This is especially dangerous when residential neighborhoods, recreational areas, or watersheds exist in close proximity to industrial or otherwise hazardous sites. A flood event that disperses toxicants in residential areas can have complex and long-lasting negative public health consequences, such as increasing the risk of waterborne disease outbreaks[21] or the incidence of chronic conditions like cancer and asthma.[22] Social and epidemiological vulnerability factors, such as income or access to health care, can amplify these effects.[23]

Due to the rising costs of disaster events associated with weather and climate, the US Government Accountability Office (GAO) issued recommendations for concerted planning and investment to address climate change-related risks and build resilience.[3] The Federal Emergency Management Agency (FEMA) developed a geographic information systems (GIS) based tool that provides layers for community resilience indicators such as infrastructure locations and historic hazard data.[24] In 2019, Teron, Louis-Charles, and Nibbs, et al. developed a Toxics Mobility Inventory (TMI) that uses GIS analysis to guide planning and remediation activities for contaminated sites to promote community resilience.[25] In both cases, GIS is used to inform decision making by facilitating the integration of spatial datasets with different data types and scales.

The TMI provides a framework of categories involved in a nexus of risk defined by weather hazards, extant toxics, and social vulnerability and estimates the potential multiplicative effects resulting from their spatial relationships over time, allowing for both spatial and temporal analysis and forecasting.[26] The TMI's test case for measuring the threat of transferral of hazardous substances is limited to existing Superfund sites (with a two-mile buffer) layered with choropleth maps showing individual race ("percentage of people of color") and income ("annual household income at or below $25,000"). Therefore, the TMI needs further testing to: 1.) identify the most relevant variables from its broad list of example indicators, 2.) identify tools for overlay and integration of those variables, and 3.) utilize its capabilities within existing advanced digital analytical tools.

To address these gaps, GIS and Toxicological Prioritization Index (ToxPi) software[27] was used with the TMI to integrate multiple datasets and measure the relative individual and combined effects on vulnerability of variables across the hazards-toxics-social nexus (e.g., floodplain area, industrial land use, social vulnerability measures) and their spatial heterogeneity across US Census tracts. A Toxics Mobility Vulnerability Index (TMVI) was developed and applied to Harris County, Texas, to assess the risk to residents from the transfer of toxic materials during a flood event. The TMVI uses publicly available data to provide a new perspective for both researchers and policy makers tasked with preparing for and mitigating complex and overlapping risks.

Materials and Methods

Data for five variables corresponding to the TMI categories were selected for the TMVI, including three spatial attributes (measured as percent of land area) and two sets of population vulnerability factors (social vulnerability and underlying health concerns, measured via "flag scores" and prevalence, respectively) (Table 1). Data were gathered from multiple locations and calculated using GIS software to derive comparable measures for each of 786 US Census tracts in Harris County. US Census tracts were selected as the unit of analysis because they are the smallest geographic unit at which many of the data are available. Whenever possible, 2016 data were used, including for the delineation of the tracts. The following sections describe each variable in greater detail, along with the procedure used to combine them into the overall TMVI.

Spatial Data

The extent of legacy and current pollution in industrial areas of Harris County has been well documented.[25,28,29] Industrial zones are included in the TMVI as a primary source for toxic materials that may be transferred throughout a US Census block by floodwaters during a flood event. To calculate the proportion of each census tract designated for industrial land use, a parcel-scale land use shape file was downloaded from the Harris County Appraisal

Table 1. Categories and Example Indicators for the Toxics Mobility Inventory (TMI) and Selected Variables for the Toxics Mobility Vulnerability Index (TMVI)

Category (TMI)[a]	Example Indicator (TMI)[a]	Selected Variable (TMVI)[b]
Toxic Sites	Prevalence of legacy pollution in coastal communities	Industrial land (% land area)
	Profile of toxins (behavior)	
Social	Population density of coastal community	Social Vulnerability Index (SVI) "flag score"
	% of population with health insurance	
	% of population living below poverty line	
Climate Change	Exposure to tropical storms	100-year floodplain (% land area)
	Flood plain status	
Emergency Response	Protective gear and equipment	Health outcomes (prevalence of underlying health concerns)
	Hazmat training & planning	
Topography	Impermeable surface cover	Impermeable surface (% land area)
	Combined sewer overflow potential	

[a]Teron and colleagues' suggestions for Toxics Mobility Inventory (TMI), drawn verbatim from Teron et al., Table 2, p. 229.[25]
[b]Authors' selections for variables to include in the Toxics Mobility Vulnerability Index (TMVI).

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District and parcels designated as industrial were isolated to create a simplified industrial land use layer for the entire county.[30] This industrial land use layer was combined with a layer delineating the county's 786 US Census tracts and used to calculate the proportion of industrial land in each US Census tract.

Floodplains are areas that have been designated to be at increased risk for flooding, especially during extreme weather events.[31] Although floodplains can be delineated for any number of return period flood events, the most commonly used is the 100-year floodplain, which demarcates the area within a community that ostensibly has a 1 percent chance of flooding in a given year. Since flooding may play an important role in the transport and fate of toxics across a community, the proportion of each US Census tract in the 100-year floodplain was derived from a FEMA floodplain shape file for Harris County[32] combined with the US Census tract shape file.

While natural areas and green infrastructure can attenuate and filter floodwater, impervious surfaces (e.g., asphalt, concrete, roofing materials) have the opposite effect, preventing the absorption of floodwater and intensifying flooding.[33] Some impervious surfaces may also be sources of pollutants, for example, from the accumulation of leaked automobile fluids on a typical parking lot.[34,35] The extent of impervious surface area is derived from a national Land Use/Land Cover raster file. After extracting the data for Harris County, green and natural land cover categories (including deciduous forest, evergreen forest, mixed forest, shrub/scrub, herbaceous hay/pasture, cultivated crops, woody wetlands, and emergent herbaceous wetlands) are isolated and converted to a polygon shape file. When combined with the layer, the proportion of each US Census tract that is in green or natural space, as well as its inverse—the proportion covered by impervious surfaces—can be calculated.

Population Vulnerability

Characteristics related to social vulnerability may exacerbate both the immediate and long-term impacts of flooding and the transfer of toxic materials. Therefore, in addition to spatial data, data were acquired for a set of 15 individual variables organized in four themes (socioeconomic status, household composition and disability, minority status and language, and housing and transportation) that make up the Centers for Disease Control and Prevention's (CDC) Social Vulnerability Index (SVI).[17,36] A shape file containing SVI data at the US Census tract scale for the year 2016 was downloaded from the SVI website for the state of Texas and then clipped to the Harris County study area.[37]

As with social vulnerability characteristics, the prevalence of chronic diseases and lower self-reported physical and mental health status and access to health care can exacerbate the impacts of flood-transferred toxics. Prevalence data were obtained to characterize overall health from the CDC for 13 key health outcomes, including the incidence of high blood pressure, cancer, asthma, coronary heart disease, chronic obstructive pulmonary disease, diabetes, high cholesterol, kidney disease, obesity, stroke, poor mental health, poor physical health, and lack of health insurance.[38] Data tables containing this information at the US Census tract scale for the largest cities within Harris County are downloaded in .csv format from the CDC's Disease and Health Promotion Data & Indicators website[38] and spatially joined to the US Census tract shape file to facilitate combination with the other data.

ToxPi

Once the data are derived, cleaned, and spatially assigned to US Census tracts using GIS software, the entire dataset is input into the ToxPi program, developed by researchers at North Carolina State University and Texas A&M University.[26,39–42] ToxPi is then utilized to generate a TMVI score for each US Census tract as well as a corresponding "pie" that displays the relative values of each of the five TMVI variables. ToxPi calculations normalize the input data for each variable, using the relative score for each tract to determine the size of the "slice" and the rank in relation to the other tracts, producing a pie and rank for each census tract. The higher the overall score, that is, the higher its average relative score for each input variable, the larger the pie and the higher its rank. Thus, tracts with higher scores (larger pies) can be seen as more vulnerable to the transfer of toxics during a flood event than those with lower scores. The relative size of individual slices provides similar information regarding the relative effect of the corresponding variable on vulnerability in a given US Census tract.

ToxPi software also allows the weighting of variables. For this analysis, each of the five variables is given equal weight relative to the others, such that each counts for 1/5 of the total TMVI score. The three spatial variables—industrial land area, floodplain area, and impervious surface area—are each given full weight (1/5 of the pie) due to their role as primary source of toxic materials and the role they play related to the potential volume and velocity of water. The individual factors in the compound variables, however, are weighted to reflect that the compound variable is made up of multiple, equally contributing elements so that each compound variable (slice) retains a total weight of 1/5 of the total pie. For example, since the SVI is comprised of four themes that together constitute a set of key indicators of the social vulnerability status of a population, the ToxPi calculation for each of these themes is calculated separately, but weighted at 1/20 (5% or 1/4 of the 1/5 share), so that the total influence of the social vulnerability variable remains at 1/5 of the ToxPi score.

The health outcomes variable is composed of 13 separate factors corresponding to the prevalence of 13 key health concerns among the resident population of the US Census tracts. To ensure that the health outcomes category is equally weighted, each of the health outcomes is weighted at 1/65 ($\sim$1.5%; 1/13 of the 1/5 share). Thus, the health outcomes, as a whole, count for 1/5 of the total TMVI score, even while the individual variables are assessed and calculated separately.

*ToxPi*GIS*

The TMVI results were also input into the online ToxPi*GIS program (http://gistoxpi.jigsy.com), which enables the geolocation of the pies on top of their corresponding US Census tract. This dynamic platform allows for a simultaneous and interactive visualization of a GIS-linked choropleth map showing the total TMVI score for each tract and the corresponding ToxPi pies.

Results

The mean TMVI score for Harris County is 0.359 (median: 0.348), which is the average of the normalized input variables (Table 2). This serves as a baseline for understanding the contributions to vulnerability of individual variables created from the five datasets, normalized to facilitate comparison and indexing at the US Census tract. Since the unit of analysis is the US Census tract, an average score below 0.5 indicates that more tracts have lower TMVI scores than those that have higher scores and that individual variable averages are more often low than high (Table 2).

Industrial land use is relatively concentrated in Harris County and is the primary source for transferable toxic materials. The TMVI score of 0.126 (median: 0.064) is lower than the overall score. While these potentially toxic parcels are only a small proportion of the total land area of a typical Harris County census tract (mean: 7.4%; median: 3.7%), they are concentrated in a relatively few tracts, with 60 out of 786 tracts in Harris County having more than 25 percent industrial land use. However, even this relatively concentrated land use pattern leaves low levels of industrial land use spread throughout Harris County (Figure 1) and the risk of toxics transfer is therefore present in many locations.

The average TMVI score for floodplain area is 0.188 (median: 0.096). As with industrial land use, the 100-year floodplain is relatively concentrated—in this case, following the river and bayou network—but spread throughout Harris County. Given the low-lying topography and abundance of tributaries, nearly 20 percent of the average Harris County US Census tract is located within the floodplain, and in more than 80 tracts more than 50 percent of the land is designated as being in the floodplain. This places many areas at increased risk for the transfer of toxic materials, especially when industrial land uses are located in proximity to other land uses like recreation areas or residential housing inside the

Table 2. Toxics Mobility Vulnerability Index (TMVI) Variables and Descriptive Statistics for Harris County, Texas

Variable	TMVI (Normalized Values)				Non-Normalized		
	Mean	Median	Std. Dev.	Weight	Mean	Median	Std. Dev.
Industrial land area (%)	0.126	0.064	0.163	20%	7.4%	3.7%	9.6%
Floodplain area (%)	0.188	0.096	0.231	20%	18.8%	9.7%	23.1%
Impermeable surface area (%)	0.895	0.982	0.177	20%	90.1%	98.3%	16.7%
Social vulnerability ("flag score")	0.162	0.091	0.204	20%	1.78	1.00	2.24
Health outcomes (prevalence)	0.466	0.548	0.296	20%	n/a	n/a	n/a
Overall TMVI	*0.359*	*0.348*	*0.112*	*100%*	n/a	n/a	n/a

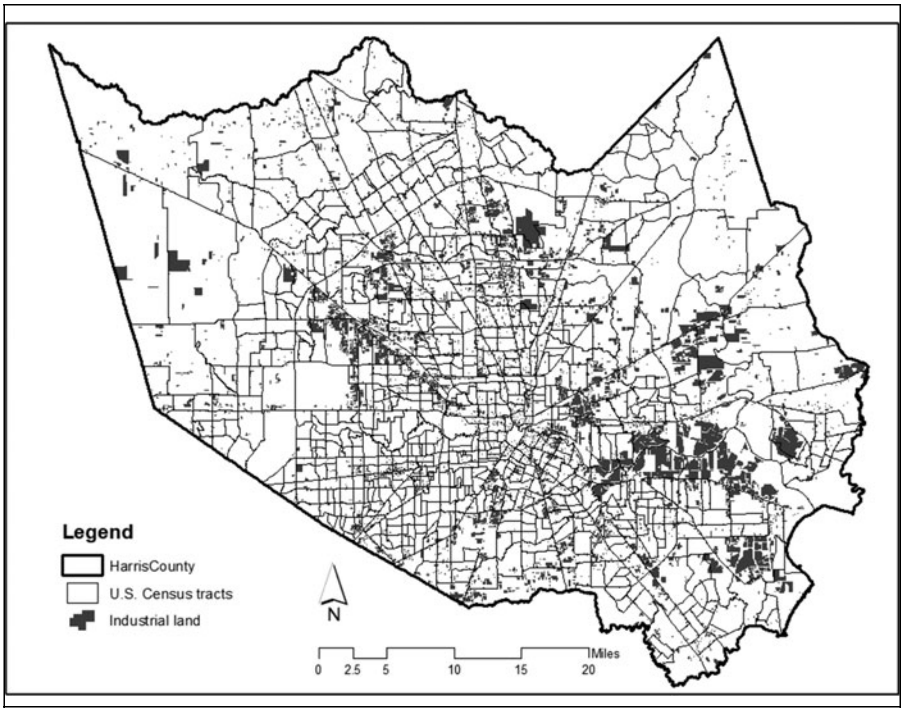

Figure 1. Location of industrial land use in Harris County, Texas

floodplain. Because floodplains and industrial land areas frequently overlap, these combined risks can add to a US Census tract's overall vulnerability.

The mean TMVI score for the impervious surface area variable is 0.895 (median: 0.982). Impervious surfaces can facilitate the transfer of toxics across a landscape by helping to speed floodwaters and leading to sheet flow, as well as by preventing attenuation and filtering of the floodwaters and anything they are carrying. Impervious surfaces cover an average of 90.1 percent of Harris County US Census tracts, which is not surprising given the region's history of rapid and often poorly regulated development.

Social vulnerably and poor health have been shown to exacerbate the acute and chronic effects of hazards like flooding and the spread of toxic materials on population health.[5] Social vulnerability has a low mean TMVI score, 0.162 (median: 0.091), indicating it is highly concentrated and inequitably distributed in Harris County. For example, only 100 tracts have five or more flags, while 309 have no flags at all. The average composite health outcomes variable score is 0.466 (median: 0.548), suggesting a somewhat more diffuse pattern of negative underlying health factors across Harris County. Overall prevalence of negative health outcomes is higher in the northern, southern, and eastern sections of Houston, which may indicate increased vulnerability when tracts in these areas align with high concentrations of the other TMVI variables. Often overlooked when considering natural hazards risk, underlying health conditions can be critical moderating factors when exposure to toxic materials makes a natural disaster a compound disaster.

The highest overall TMVI scores are concentrated in census tracts surrounding central Houston, especially in the northern and eastern sections of the city. Eight of the 10 most vulnerable tracts in all of Harris County are located in these areas. In the most vulnerable US Census tracts, impervious surface area is ubiquitous, appearing as a large "slice" in all of the TMVI "pies" (Figure 2). Floodplain area is also present in all of these most highly vulnerable tracts, though to a greater degree in some than in others. High concentrations of industrial land area make several of these US Census tracts particularly vulnerable. The population characteristics captured in the social vulnerability and health outcome variables are found in all 10 tracts. Therefore, even in tracts that do not contain a large proportion of industrial land uses, the combination of threats from other variables means that areas without large industrial land use slices remain at significant risk due to their high social vulnerability, poor health status, and exposure to the 100-year floodplain.

Discussion

The TMVI advances the TMI by presenting a set of indices for measuring the threat of toxic materials transfer during flood events. These indices can be overlaid using digital tools to visualize the TMVI, including the relative importance of contributing factors and the heterogeneity of risk. When applied to Harris County to assess the potential threat of hazardous substance transfer during flood events, the TMVI demonstrates the variability of vulnerability by US Census tract. Although impervious surfaces are ubiquitous, more socially vulnerable US Census tracts in Harris County are more highly threatened by industrial land uses and flooding. These exposures are potentially exacerbated by the higher prevalence

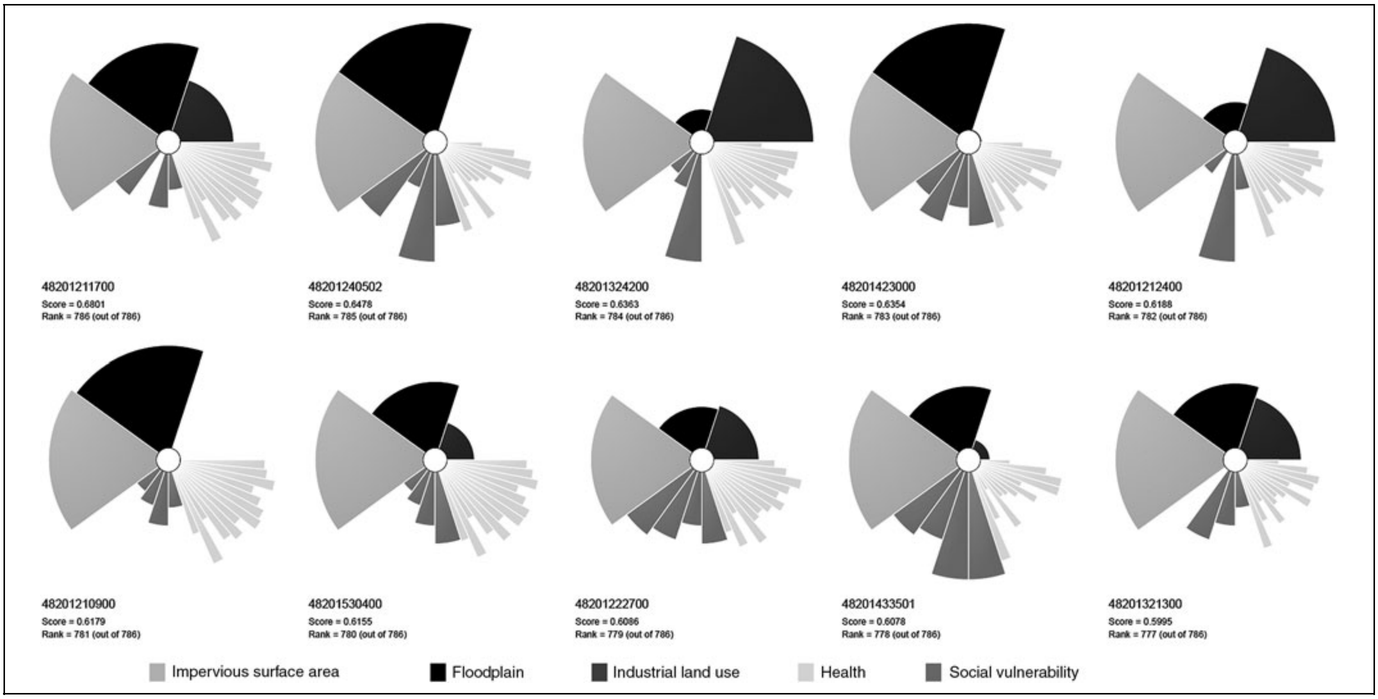

Figure 2. ToxPi visualization for the 10 Harris County census tracts most vulnerable to the transfer of toxic materials during a flood event, according to the Toxics Mobility Vulnerability Index (TMVI).

of negative public health conditions in these same US Census tracts, such as obesity.

The TVMI also allows researchers, decision makers, and policy makers to better understand the dynamics of complex exposures, identifying locations that are particularly vulnerable as well as influential variables (and combinations thereof) upon which planning and public health interventions can be based. The overall mean TMVI score of Harris County, considered to be relatively vulnerable based on a number of separate measures (e.g., percent floodplain, concentration of industry, high levels of social inequity), could be compared in future studies to the overall mean scores of other US jurisdictions to give a sense of relative vulnerability, a potentially useful indicator for researchers and state or federal policy makers. With the capability to spatially locate areas with the highest relative risk for toxicant transferral during flooding and to calculate contribution of various factors to those risks, both residents and governmental authorities can better target solutions to address such conditions.

For example, new policies that encourage investments in infrastructure and incentives related to increasing open space would benefit Harris County by lessening runoff amounts, offering open space to improve the physical health of community members, and providing natural remediation to industrial runoff. A sprawling landscape, which includes a high proportion of impervious surface, is an important driver of the increased frequency and severity of flooding in the region.[43] In Harris County, pervious surface area and green infrastructure (GI) is heavily concentrated in about a dozen large census tracts in the outer, mostly undeveloped (also known as greenfield) areas, where it covers over 70 percent of the land mass. By contrast, pervious surface area is relatively rare in the central city; 564 of the 786 tracts in the county contain less than 10 percent, and 155 of those contain essentially no green space. Put simply, US Census tracts in Harris County contain an average of 9.9 percent green space, compared to 18.8 percent floodplain.

It has been widely recognized that socially vulnerable populations have less capacity to withstand, absorb, and recover from the physical impacts (e.g., displacement, property loss) associated with natural disasters like flooding. However, when flooding may involve toxicant transferral, the challenges of estimating relative risk become even more critical to address due to the highly inequitable distribution of toxic sites in environmental justice communities and the increasing frequency and severity of natural disasters that beget compound disasters due to anthropogenic processes.[5] The limited capacity and funding of the US emergency preparedness and response system necessitates new tools be developed and used by both researchers and practitioners to prioritize mitigation investments in areas, and among individuals, at the highest risk across the hazards-toxics-social nexus.

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